DRAFT 5/2/00
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Consumer Choice of Food Products and the Implications for Price Competition and Government Policy

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Selected Paper
Presented at the Conference
The American Consumer and the Changing Structure of the Food System
May 3-5, 2000
Washington D.C.

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Introduction

The growth in consumer demand for high quality products is causing changes in the functioning of the food processing and marketing sectors and in government regulation of these sectors. Food companies, motivated by increased profitability derived from the supply of quality-differentiated products, are increasingly promoting the taste, convenience, nutritional, and safety attributes of their products. At the same time, because food companies may fail to provide socially optimal levels of quality and may exploit product heterogeneity to reduce price competition, government regulators want to ensure high levels of food product quality as well as ensure a competitive environment in the industry.

These issues are important in the U.S. prepared frozen meals industry. Current consumption trends show that Americans eat more foods at home that have been prepared elsewhere, and increasingly rely on convenience items in foods eaten at home. Recent scanner data show that 89% of U.S. households purchase prepared frozen meals at grocery stores. For our analysis, we include frozen dinners and entrees, and frozen pizza in the prepared frozen meals category. In 1999, retail sales of frozen dinners and entrees were $5.2 billion and of frozen pizza were $2.2 billion. These categories are growing at an annual rate of 12%, the fastest in the frozen foods department (IRI, Inc. 1999).

The prepared frozen meals industry is notable for attempts to extend the variety of food product offerings, including nutritionally improved versions of foods, and for the aggressive marketing of these foods to American consumers. On average, the number of brands offered for sale in this category is 340 and the advertising to sales ratio is 6.8%. In addition, the degree of concentration in this industry is high, with the three leading firms (Campbell Soup Co., Nestle, and ConAgra) accounting for about 65% of total retail sales.

In this study, we investigate what affected consumer demand for prepared frozen meals in the period from 1993 to 1998, when government regulation of labeling on the nutritional quality of foods was changing. We use estimated demand parameters to evaluate the effectiveness of the new mandatory nutrition labeling policy and to assess the impact of consumer demand on manufacturers' marketing strategies and price competition in the industry. In a changing market for food product quality, an analysis of consumer demand for differentiated products is vital for understanding consumer preferences and changes in preferences as well as for understanding firms' conduct. The results of our study provide information necessary for the formulation and evaluation of government policies targeted towards the industry and consumers, including policies intended to improve the health of the American public.

Our approach draws from and expands on models and methodologies for analysis of consumer and producer behavior in differentiated product markets as reported in the theoretical literature. We make particular use of the discrete choice models developed by McFadden (1978), Berry (1994), and Berry, Levinsohn, and Pakes (1995). These models provide an effective approach for the theoretical modeling and empirical estimation of consumer demand and producer supply parameters in differentiated product markets and are consistent with a structural model of equilibrium in oligopolistic industries. However, to date these models have failed to account for consumer knowledge about nutrition and use of nutrition labels. Our work expands on previously used discrete choice models by assessing the effects of horizontal and vertical quality attributes more thoroughly, and by considering not only media advertising but also in-store marketing efforts. This study is the first to take into consideration consumer knowledge about nutrition and use of nutrition labels, and thus offers a more complete picture of consumer preferences and choices.

We apply a simulation technique introduced by Pakes (1986) in order to estimate consistently a random coefficients discrete choice model of consumer demand for prepared frozen meals for the years 1993-1998. We use <u>product level</u> and <u>aggregate consumer-level</u> data to obtain <u>individual consumer</u> utility parameters and their distribution in the population. We obtain own- and cross-price elasticities for frozen meal products as well as elasticities of demand with respect to individual product attributes for all the products considered. We then compute the price-cost margins for the industry implied by three hypothetical industry structures: single product firms, several firms with many products each, and a multi-product monopolist producing all the products. The estimated elasticities, together with the producer conduct parameters, play important roles in the analysis of policy issues related to producers' market power and the effectiveness of government regulation of nutrition labeling presented in the last section of the paper.

The U.S. Prepared Frozen Meals Industry

The U.S. prepared frozen meals industry can be traced back to Clarence Birdseye who started a company in New York in the early 1920s that specialized in freezing fish fillets (Frozen Food Age 1987). In the beginning, the industry was confined to the wholesale segment but in the late 1940s the retail segment became a dominant market for the industry. In the 1950s, a small number of companies that entered early maintained an advantage through heavy brand promotion activities. By the end of the decade, high expenditures on advertising were crucial to building a major position in the retail segment.

Over the next 40 years, the scale of the industry grew enormously. As noted, retail sales of frozen dinners and entrees amounted to $5.2 billion and of frozen pizza to $2.2 billion in 1999 (IRI, Inc. 1999). A small number of well-marketed national brands continue to dominate retail sales. The smaller producers concentrate on selling within special retail categories at the local or regional levels. Private label products account for 1.7% of dollar value share for frozen dinners and entrees and for 5.2% for frozen pizza. These shares remain steady.

A number of structural changes have occurred in terms of industry leadership. As the size of the industry and the range of prepared frozen meals categories expanded, some of the firms that entered the small, new segments of the market in its early years have grown to become some of today's leading firms. The most notable examples are C. A. Swanson & Sons, which introduced the "TV dinner" in 1953, and Stouffer Foods, which began producing frozen entrees in the same year. Almost all of the major firms that entered the industry did so by acquisition. Campbell acquired Swanson in 1955 (and spun it off much later in 1998) and Nestle acquired Stouffer in 1973, while Banquet, owned by RCA, was acquired by ConAgra in 1980. By the 1990s, the three leading firms had over 65% of sales in the prepared frozen meals category.

Sales of prepared frozen meals have grown steadily, driven by the aggressive marketing of existing brands and rapid introduction of new brands. There are currently over 270 brands of frozen dinners and entrees and over 70 brands of frozen pizza offered for sale in American supermarkets.[1] The brand level volume sales for prepared frozen meals vary from 5.4% for the leading brand, to

[1]We employ the definitions developed in the IRI Infoscan Data Base. Brands are defined as unique aggregates of UPC-coded products. For example, Stouffer's Lean Cuisine Lasagne is a brand in the IRI data. Individual brands are made up of one or more products that differ by variety and package size.

0.8% for the 50th brand, to less than 0.1% for the 100th brand. Not only are there many brands in the industry but the rate of introduction of new products is high and increasing over time. In 1998, 39 new brands were introduced. The most successful new products (e.g., Birdseye Chicken Voila, Stouffer's Homestyle, Healthy Choice Bowl Creations) have the following attributes: they meet consumers "do it for me" need, they are convenient, and they have "homemade" quality (NFFA 2000). In addition, the same industry study shows that consumers are switching to more expensive, higher quality, higher value, and larger products. Therefore, the average price of products sold has increased at the category level.

Competition through advertising is a characteristic feature of the industry since its early years. Presently, the average advertising to sales ratio is about 7%. The advertising to sales ratio exceeds 18% for the well-promoted brands. Additional promotional activities that are important in this industry include: in-store displays, price reductions, interactive website offerings, and two annual industry-wide promotional campaigns--the March National Frozen Food Month and the October Frozen Food Festival. In 1999, these two campaigns were run under a theme "Easy Home Meals with Frozen Food!" emphasizing consumers' needs for convenient, high quality, home-style meals.

Methods of Analysis in Differentiated Products Markets

A very important consideration in estimating demand systems is the need for flexible functional forms that do not impose strong assumptions on consumer utility and the resulting pattern of cross-price elasticities. This consideration applies to homogenous as well as differentiated product markets. However, estimating demand systems for differentiated products adds at least two additional concerns. The first concern is related to the large number of products and hence the large number of parameters to be estimated. We call this problem a dimensionality problem. This can be illustrated by the following example: a constant elasticity demand system for 100 brands requires estimating 10,000 elasticities. The second concern in estimating demand systems for differentiated products is related to consumer heterogeneity. If consumers were identical we would not observe so many different products in today's marketplace. In the literature, researchers have developed three basic methods that deal with these two concerns. Below we discuss each of these methods in turn.

Symmetric Representative Consumer Methodology

In this approach researchers assume that consumer preferences are of the "right" Gorman form (Gorman 1959), and that an aggregate or an average consumer exists and has a demand function that satisfies conditions specified by economic theory (Dixit and Stiglitz 1977, Spence 1976). A common specification of the utility function in this case is a constant elasticity of substitution (CES) utility function. A demand function for a representative consumer is then derived from the CES function. The dimensionality problem is solved by imposing symmetry between different products, therefore, a single parameter (the price elasticity) is estimated, regardless of the number of products, using non-linear estimation techniques. The symmetry condition is very restrictive and the cross-price elasticities are restricted to 1.

An alternative to the CES utility function is a function used by Anderson, de Palma, and Thisse (1989) that yields the logit demand system. Here estimation involves as many parameters as the number of products and allows for more realistic substitution patterns. However, the estimated elasticities are functions of market shares only and are not related to the characteristics of products. In fact, both of these specifications (the CES and the logit) do not deal well with closeness of products in the attribute space and they do not explicitly consider consumer heterogeneity.

Multi-Level Demand Methodology

Another way of solving the dimensionality problem is to divide the products into smaller groups and allow for a flexible utility function within each group. The validity of this procedure relies on two assumptions: the separability of preferences and multi-stage budgeting. If the separability of preferences assumption holds then the products can be grouped into segments so that preferences within each segment are independent of the quantities in other segments. Multi-stage budgeting occurs when the consumer can allocate total expenditures in stages: at the highest stage to broad categories, then to segments, and finally to individual products. Separability and multi-stage budgeting are related in that separability is a necessary and a sufficient condition for the last stage of multi-stage budgeting.

Originally, this method was developed for the estimation of fairly broad product categories. In their recent work, Hausman, Leonard, and Zona (1994), Hausman (1996), and Cotterill (1996) use these ideas to construct multi-level demand systems. Their actual applications involve a three-stage system: the top level corresponds to the overall demand for the product category (e.g., cereal); the middle level corresponds to the demand for different market segments (e.g., cereal for adults, cereal for children); and the bottom level corresponds to the demand for specific products or brands. This segmentation of the market reduces the number of products proportionally to the inverse of the number of segments. Therefore, with either a small number of brands or a large number of segments this method can use flexible parametric functional forms (e.g., AIDS) to give good approximations to any demand system. However, as the number of brands in each segment increases, this method becomes less feasible. In this sense, the multi-level demand system does not really solve the dimensionality problem but merely decreases its effects.

The choice of functional form is determined by the need for flexibility, but it also requires that the conditions for multi-stage budgeting are met. It appears that empirical applications are not consistent with the theory of exact multi-stage budgeting (Nevo 1997). In addition, the demand functions within segments of products are flexible but the division into segments can be very restrictive. This can result in low cross-price elasticities between brands in different segments. Finally, the multi-level demand system does not model and identify the distribution of consumer heterogeneity.

Discrete Choice Methodology

The two methods discussed above deal with the large number of products by essentially aggregating them into groups. However, in studying demand for differentiated products it is exactly the substitution between single products or brands that is of interest. Also, in these methods demand is specified for an aggregate consumer so consumer heterogeneity is not explicitly addressed. For these reasons, these methods are of limited usefulness in estimating a demand system for differentiated frozen meals.

The discrete choice approach is a third, alternative method of modeling consumer demand; it dates back to McFadden (1978). Here consumer preferences for differentiated products are specified as functions of individual consumer characteristics and of product attributes. Therefore, the dimensionality problem is solved by projecting the products onto a space of product attributes making the relevant dimension that of this space and not of the square of the number of products. In addition, consumer heterogeneity is modeled explicitly and unknown parameters of the distribution of heterogeneity are estimated. However, a major criticism of this methodology concerns its heavy reliance on functional forms. Recent work has shown how this limitation can be overcome and plausible substitution patterns can be estimated (Cardell 1989, Berry 1994, Berry, Levinsohn, and Pakes 1995).

Our objective is to estimate own- and cross-price elasticities as well as elasticities of demand with respect to product attributes for all of the frozen meal products considered. The resulting estimations allow us to evaluate the implications of these elasticities for both price competition within the industry and for government policy. The discrete choice method is the only one suitable to this purpose because it allows us to obtain elasticities for single products that are driven by consumer heterogeneity.

A Discrete Choice Model of Consumer Demand for Prepared Frozen Meals

To obtain our demand system for differentiated prepared frozen meals, we use a discrete choice model of individual consumer behavior (see McFadden 1978, Berry 1994, Berry, Levinsohn, and Pakes 1995, Nevo 1997, as well as the product differentiation literature by Shaked and Sutton 1982, Perloff and Salop 1985, Bresnahan 1987). We then apply the estimated parameters of the demand system to evaluate price competition in the industry and the effectiveness of mandatory nutrition labeling policy.

Discrete choice models utilize indirect utility functions and assume that the level of utility that a consumer derives from a given product (brand) depends on both product characteristics and consumer characteristics. Therefore, we specify the maximum utility derived by consumer i from consuming product j in time period t as:

(1) $$u_{ijt} \quad {}_{k}\, x_{jkt}\beta_{ik} \quad \xi_j \quad \Delta\xi_{jt} \quad \varepsilon_{ijt}$$

where

$$(2) \qquad \beta_{ik} \;\; \bar{\beta}_k \;\; \underset{r}{} D_{irt}\beta^{m}_{kr} \;\; \beta^{um}_{k} v_{ik}.$$

The products competing in the market are indexed as j=0, 1,..., J. Product j=0 is the outside good, so that u_{i0} is the utility the consumer derives if she does not purchase any of the J brands and allocates her income to other purchases.[2] The x_{jkt}'s are observed product characteristics, including price. The ξ_j is the national mean of the unobserved product characteristics and the $\Delta\xi_{jt}$ is a quarter specific deviation from this mean. The β_{ik}'s are the preference parameters of consumer i for product characteristic k. The D_{irt}'s are measured consumer characteristics, where r is a consumer characteristic, including knowledge about nutrition and use of nutrition labels, and v_{ik}'s are unmeasured consumer characteristics. Therefore, the β_{ik}'s are made up of a first component that captures the average consumer's preferences for an attribute and a second component that represents the deviation of individuals from the average preference based on their own characteristics. This latter component is made up of deviations based on both measured (m) and unmeasured (um) consumer characteristics. Finally, the ε_{ijt}'s represent error terms in individual preferences and are assumed to be independent of the product attributes and of each other.

We find the consumer level choice model by substituting equation (2) into equation (1) to obtain:

$$(3) \qquad u_{ijt} \;\; \delta_{jt} \;\; \mu_{ijt}, \; for \; j \;\; 0, \; 1, \ldots, \; J,$$

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[2]Based on equation (1), consumer utility derived from the outside good can be specified as: $u_{i0t}=\xi_0+\pi_0 D_i+\sigma_0 v_{i0}+\varepsilon_{i0t}$, where π_0 and σ_0 are the coefficients on measured and unmeasured consumer characteristics.

where

(4) $$\delta_{jt} = \sum_k x_{jkt}\bar{\beta}_k + \xi_j + \Delta\xi_{jt},$$

and

(5) $$\mu_{ijt} = \sum_{kr} x_{jkt} D_{irt} \beta^{m}_{kr} + \sum_k x_{jkt} v_{ik} \beta^{um}_k + \varepsilon_{ijt}.$$

The indirect utility of consumer i from product j in time period t is now expressed as the mean utility, referred to as δ_{jt}'s, and the mean zero heteroscedastic deviation from that mean, μ_{ijt}, that captures the effects of the random coefficients, which reflect individual consumer characteristics. In this case, the contribution of x_k units of the k^{th} product characteristic to the utility of consumer i is given by:

(6) $$(\bar{\beta}_k + \beta^{m}_{kr} D_{irt} + \beta^{um}_k v_{ik}) x_{jkt}$$

and varies across consumers. The mean of the utility from good j, δ_{jt}, is entirely determined by the product characteristics and thus represents a product specific component that does not vary with consumer characteristics. On the other hand, a deviation from that mean, μ_{ijt}, depends on the interaction between consumer and product specific characteristics. As a result, consumers who have a preference for fat, for example, will tend to attach high utility to all fatty products, and this will induce large substitution effects between fatty products. The parameters of the model are $\theta=(\delta, \beta^m, \beta^{um})$. The vector δ includes the linear parameters and the vectors β^m and β^{um} contain the non-linear parameters.

We obtain the aggregate demand system by summing the choices implied by the individual utility model over the distribution of consumer characteristics in the population. We denote the vector of measured and unmeasured individual characteristics by w, therefore,

$$(7) \qquad w \ (D, \ v, \ \varepsilon)$$

and we denote its distribution in the population by P_w.

Each consumer chooses one unit of the good that maximizes its utility, therefore, aggregate demand for good j is given by the integral of the density of consumer characteristics over the set of product characteristics that imply a preference for good j:

$$(8) \qquad s_{jt}(\delta, \ \beta^{m}, \ \beta^{um}, \ x) \quad \underset{A_{jt}}{} P_{w}(dw) \quad \underset{A_{jt}}{} P_{\varepsilon}(d\varepsilon) \ P_{D}(dD) \ P_{v}(dv)$$

where

$$(9) \qquad A_{jt}(\delta, \ \beta^{m}, \ \beta^{um}; \ x) \quad w\text{:} \quad \underset{r \ 0, \ 1, \ldots, \ J}{\max} \ [u_{irt}(w; \ \delta, \ \beta^{m}, \ \beta^{um}, \ x)] \ u_{irt} \ .$$

By multiplying the market share equation by the number of consumers in the market, M, we obtain the J-vector of demands as $M^*s(\delta, \beta^{m}, \beta^{um}, x)$. We model consumer heterogeneity as a function of the empirical non-parametric distribution of consumer characteristics without imposing any arbitrary functional forms on this distribution. Thus, given the assumptions on the distribution of the unobserved variables (v and ε), we can compute the integral in the market share equation analytically or numerically.

The Multinomial Logit Model

In order to solve the integral given in equation (8) one option is to assume that consumer characteristics or consumer heterogeneity enters the model only through the additively separable random shocks, ε_{ijt}, and that these shocks are distributed with a Type I extreme value distribution. This assumption reduces the model to the classic multinomial logit model and gives us the following market share equation:

$$(10) \qquad s_{jt} = \frac{\exp(\delta_{jt})}{1 + \sum_{j=1}^{J} \exp(\delta_{jt})}, \quad \textit{for } j = 0, 1, \ldots, J.$$

We note that, in this case, there is a closed form for the market share equation and there is no need to compute any integral.[3]

However, this specification is problematic despite its computational simplicity. The utility function is additively separable into two terms, one determined entirely by the product characteristics, δ_{jt} , and one determined by the consumer characteristics, ε_{ijt}. The utility function expressed in this form implies that all substitution effects depend only on the δ_{jt}'s. Since there is a unique vector of market shares associated with each δ-vector, the additively separable specification says that the cross-price elasticities between any two products are proportional to market shares. That is, the logit model restricts consumers to substitute toward other products in proportion to market shares, regardless of characteristics of the products. The additively separable specification also implies that

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[3]Equation (10) implies that δ_{jt}=ln(s_{jt})-ln(s_{0t}). Therefore, the estimate of δ_{jt} for the logit model is ln(s_{jt})-ln(s_{0t}), and consequently, the equation can be estimated by OLS.

two products with the same market share will have the same own-price elasticity. In an oligopoly setting, this is especially problematic because the two products would have to have the same markup over marginal cost. We expect markups to be determined by more than market shares, including the number of competing products that are close in product space and lower marginal utilities of income for consumers who buy more expensive goods. The price elasticities of the market shares defined by equation (10) are:

$$(11) \qquad \eta_{jlt} \; \frac{s_{jt}}{p_{lt}} \, \frac{p_{lt}}{s_{jt}} \quad \begin{matrix} \beta p_{jt}(1 \;\; s_{jt}), \;\; \textit{if } j \;\; l; \\ \beta p_{lt} s_{lt}, \;\; \textit{otherwise} \end{matrix}$$

and the cross-price elasticities are proportional to product market shares whereas the own-price elasticities are proportional to own prices.

The main conclusion is that the classic logit model of discrete consumer choice of products does not allow for interactions between product characteristics and consumer characteristics and that it explains differences in market shares by allowing only the mean of the utility from good j to change. Despite these disadvantages, we estimate the multinomial logit model here because it is relatively easy to estimate and provides a starting point for comparison to the random coefficients discrete choice model.

The Random Coefficients Discrete Choice Model

The main advantage of the alternative, random coefficients discrete choice model for estimating plausible demand elasticities is that in these models purchases are determined by the maximum utility for each consumer and not the mean utility. For example, the market share of products rich in fat could be higher for two reasons: a high mean of the distribution of preferences for fat or a large variance of the same distribution. In addition, the classic logit and random coefficients models have different implications for substitution patterns. The classic logit model explains differences in market shares by allowing only the mean of consumer utility to change. Therefore, if the price of a fatty frozen entree increases, the consumers who substitute away from that entree have the same marginal utility of fat as any other consumer. The random coefficients model allows different market shares to also be explained by a distribution of consumer characteristics. Thus, consumers who substitute away from a fatty entree have higher than average preference for fat and are more likely to substitute to other fatty entrees.

The random coefficients specification of the discrete choice allows for more realistic substitution patterns. However, it reintroduces the problem of computing the integral in the market share equation. We will solve this computational problem by applying a simulation technique introduced by Pakes (1986).

Data, Variables, and Estimation Algorithm

Data and Variables

To estimate the models described in the previous section, we need data for the following variables: market shares and prices of prepared frozen meal products; their product characteristics, advertising and promotion; and information on the distribution of consumer characteristics.

We obtain the data on market shares, prices, and in-store marketing efforts for prepared frozen meal products from the IRI Infoscan Data Base at the Food Markets Branch, Economic Research Service, US Department of Agriculture. These data are collected continuously by the marketing firm using scanning devices in a national random sample of supermarkets located in 64 metropolitan and rural areas of the United States. We calculate market shares by converting the aggregate national quarterly volume of product sales into the number of servings sold and dividing them by the total potential number of servings in a quarter. This potential is assumed to be one serving per person per day.[4] The outside good market share is defined as the residual between one and the sum of the observed market shares. The results presented below are computed for the 200 frozen dinner, entree, and frozen pizza products with the highest national market shares in each quarter from 1993 to 1998.

We obtain the price variable by dividing the quarterly dollar sales for each product by the number of servings sold and we deflate it by the Consumer Price Index.[5] The dollar sales are calculated using the real average pre-manufacturer coupon transaction prices paid by consumers. The dollar sales data do not account for the value of coupons that might be used by consumers. However, if coupons are used uniformly across products this will not affect our analysis.

The IRI data contain information on in-store marketing efforts. We use percent of dollars price reductions, percent of dollars in-store displays, and percent of dollars in store featuring to evaluate the impact of these variables on consumer choices of prepared frozen meals. The variation in these variables are shown in Table 1.

We match the Infoscan quarterly market share, price, and other data for each product with four other data sources. First, we match the IRI data with the quarterly expenditures on advertising for these products taken from the Leading National Advertising data base for 1993-1998. These data have been collected for 11 different types of mass media (e.g., network television, spot television,

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[4]The total market size is defined as τ*population*365/4, where τ=1. Alternatively, τ could be estimated.

[5]Contact the authors for an Appendix with a detailed description of the variables.

cable networks, national spot radio, network radio, newspapers, magazines). We use only the total average advertising expenditures on all of the 11 types of mass media (see Table 1).

Table 1. Market Shares, Prices, Advertising, and Promotion of Products in Sample.

Variable	Mean	Standard Deviation	Min	Max
Prices ($ per serving)	2.00	2.09	0.38	12.29
Share within Frozen Prepared Meals Market (%)	0.36	0.82	0.04	2.7
Price Reduction (% $)	14.01	5.16	0.41	43.99
Display (% $)	3.08	3.06	0.10	17.00
Feature (% $)	13.80	18.94	0.29	45.44
Advertising (Million $)	0.09	0.12	0.00	3.44

Second we match the IRI to the Nutritional Labeling Data developed at the University of Massachusetts. The National Infoscan Data do not provide information on the amounts of nutrients in food products. Thus, the information on market shares and prices has to be matched with information on the nutritional content of the respective frozen dinner, entree, and frozen pizza products. The Nutritional Labeling Data include a complete census of all products in the most popular package size offered in 33 food product categories in a representative super-store in New England for the years 1992 through 1999. These data were not collected in 1996 and 1998. Because nutritional profiles were changing slowly during this period (Mojduszka et al. 1999), we use 1997 nutritional data for 1996 and 1999 data for 1998. Although the quality change data set provides information on all the products offered in a large super-store, it does not contain information on all the products offered at the national level. As a result, some products that appear in the scanner data are missing in the supermarket data. In such cases where it is impossible to match the respective products exactly, we create the average nutrient content values for the missing products based on similar products and use these values in our estimations. Table 2 summarizes the extent of the data match between the two data sources.

Table 2. Summary of Matched Scanner Data to Nutritional Labeling Data.

	# of Scanner Observations (Per Quarter 1993-1998)	# of Observations Matched to Nutritional Labeling Data					
		1993	1994	1995	1996[a]	1997	1998[a]
Frozen Entrees and Dinners	186	124	130	128	131	131	134
Frozen Pizza	14	9	8	10	9	9	10
TOTAL	200	133	138	138	140	140	144

[a] Due to the lack of availability of 1996 and 1998 supermarket data, 1997 nutrition label data are matched to the 1996 scanner data and 1999 is matched to 1998.

In our discrete choice model of consumer demand, we include the following nutrient content variables: calories, fat, cholesterol, sodium, fiber, protein, and vitamins A and C. The levels of nutrient content variables for each product in the data set are based on standardized serving sizes that correspond to the reference amounts consumed on average by an adult person as defined under the Nutrition Labeling and Education Act (NLEA). The levels of nutrients were converted to the corresponding reference amounts if the serving size stated on the product label was not equal to the reference amount. This conversion allows comparison of different products for their nutritional content. In addition, we create two product specific dummy variables that reflect further quality attributes of frozen meal products. These two attributes are whether the product contains meat or not and whether it is an ethnic food or not. Table 3 provides statistics for the attributes for the sample of 200 products of prepared frozen meals used in the analysis below.

Table 3. Summary of Statistics on Characteristics of Products in Sample.

Variable	Mean	Standard Deviation	Min	Max
Calories	185.76	54.07	68.75	550.00
Fat (g)	7.42	4.65	0.63	30.00
Cholesterol (mg)	22.34	13.52	4.16	108.33
Sodium (mg)	434.03	158.54	195.45	1033.33
Fiber (g)	1.92	2.49	0.00	3.45
Protein (g)	8.81	3.15	0.53	23.33
Vitamin A (%)	7.82	11.03	0.00	48.78
Vitamin C (%)	4.24	4.22	0.00	15.91
Calcium (%)	6.90	6.49	0.00	29.55
Package Size (oz)	13.01	8.35	5.00	96.00
Meat Dummy (=1 if contains meat)	0.64	0.48	0.00	1.00
Ethnic Dummy (=1 if ethnic food)	0.24	0.46	0.00	1.00

Third we obtained information on the distribution of consumer knowledge about nutrition and nutrition label use by sampling individuals from the Diet and Health Knowledge Survey (DHKS) for the 1994-1996 time period. We assume that consumer knowledge and label use did not change in 1993-1994 and in 1996-1998. Therefore, we apply the 1994 data for 1993 and the 1996 data for 1997 and 1998. The DHKS surveys 1,966 individuals, 20 years of age or older, who are the main meal planners in their households. The survey includes their answers to questions concerning attitudes toward and knowledge of nutrition, food safety, and diet and health, as well as their use of nutrition labels. Here we use only those questions from the DHKS that relate to fat and nutrition panel use because we hypothesize that fat plays an important role in consumer choices of prepared frozen meals, as does knowledge about fat and use of nutrition panels. The latter can allow consumers to precisely evaluate the nutritional quality of foods they choose. All packaged foods have been required to carry nutrition panels since May 1994.

Consumer knowledge cannot be directly observed but only indirectly measured using observed responses to the specific questions. In the survey, there are six questions with regard to general knowledge about fat. We construct a binary "General Fat Knowledge" variable equal to 1 if the response to four or more questions is positive and zero otherwise. Examples of questions on general knowledge about fat include: Which has more fat, yogurt or sour cream? Hamburger or ground round? We also construct a binary "Specific Fat Knowledge" variable equal to 1 if the answer to four out of five questions regarding more specific knowledge about fat is positive and zero otherwise. Examples of questions on specific knowledge about fat include: If a food has no cholesterol is it also low in saturated fat? And is cholesterol found in vegetables/vegetable oils? In addition, we construct a third binary variable "Nutrition Panel Use." This variable accounts for consumers' use of nutrition panels and equals one when the answer to the question, do you use the nutrition panel, is yes (even if consumers state that they use nutrition panels sometimes or rarely) and zero otherwise. By incorporating this information in our model, we are able to estimate how consumer knowledge of fat and use of nutrition panels affect consumer choices of prepared frozen meal products. We assume that the consumer knowledge variables and nutrition panel use are exogenous to our demand system.

Fourth, and finally, we obtain information on the distribution of consumer demographic variables by sampling individuals from the March Current Population Survey (MCPS) for each year. Consumer per capita income is constructed by dividing household income by the size of the household. The MCPS data are representative of the national population statistics from the Bureau of the Census. Table 4 reports the sample statistics on consumer knowledge about fat, consumer use of nutrition panels, and consumer demographics.

Table 4. Fat Knowledge, Nutrition Panel Use, and Demographic Variables.

Variable	Mean	Standard Deviation	Min	Max
General Fat Knowledge	0.75	0.65	0	1
Specific Fat Knowledge	0.61	0.53	0	1
Nutrition Panel Use	0.76	0.80	0	1
Income ($)	14, 698	12,362	0	190,000
Household Size	2.79	1.75	1	11
Age	32	29	22	89

The Estimation Algorithm

Aggregate demand is a complicated function in the random coefficients discrete choice specification; linear and non-linear parameters are present. This is due to the discrete choice set for each individual and the interaction of individual and product characteristics. In addition, we distinguish between observed and unobserved product attributes. The unobserved product attributes reflect the difficulty in quantifying aspects of consumer taste and past experience, as well as firms' reputations. If unobserved characteristics are important in consumer choices of food products, prices will be correlated with the unobserved characteristics, and the estimates of price elasticities will be biased.

Our product level data allows us to control for unobserved attributes by constructing product specific dummies and introducing them into the demand equation. Product specific dummies measure consumer mean utility and contain the linear utility components of product characteristics. The dummies capture characteristics that do not vary with individual consumer tastes and, therefore, can be treated as fixed product effects. By including product specific dummies, we account for the correlation between the unobserved quality and prices. The error term is no longer the unobserved quality but it is a quarter specific deviation, $\Delta\xi_{jt}$, from this unobserved national mean. The orthogonality between $\Delta\xi_{jt}$ and the x-vector cannot be used for estimation without first transforming the observed characteristics into a linear function of $\Delta\xi_{jt}$. Berry (1994) proposed a transformation that does just that.

Berry's method, which we adopt in this paper, relies on a formation of a Generalized Method of Moments (GMM) estimator. The procedure depends on computing the implied error term for a given value of the unknown parameters and then interacting the error term with instruments thus forming the GMM objective function. The implied error term is computed by inverting the market share function to obtain the vector of mean utilities that equates the observed market shares to the predicted market shares. This is done by solving the implicit system of equations for each market

(12) $$s_t(\delta_t;\ \theta_2) \quad S_t.$$

After this inversion is performed the error term is defined as

$$\omega_{jt} = \delta_{jt}(S_t;\ \theta_2) - (x_j\beta + \alpha p_{jt}). \tag{13}$$

Only the observed market shares enter this equation. For a given value of the non-linear parameters, θ_2, we compute the mean utility, δ_{jt}, that would make the predicted market share equal to the observed market share. The residual is then defined as the difference between this mean utility and the one predicted by the linear parameters, α and β. The GMM estimator, defined as

$$\hat{\theta} = \underset{\theta}{argmin}\ \omega(\theta)' ZA^{-1}Z' \omega(\theta), \tag{14}$$

minimizes the distance between these different predictions.

The estimation method can be summarized in the following steps. First, for a given value of θ_2 and δ, we compute the market shares implied by equation (8). Second, for a given value of θ_2 we compute the δ vector that equates the market shares obtained in step one to the observed shares. Third, for a given value of θ, we compute the error term to interact it with instruments and obtain the value of the GMM objective function. Fourth, we search for the value of θ that minimizes the objective function from step three. We utilize a Matlab computer program to perform all the estimations and calculations (see also Nevo 1998).

Estimation Results and Analysis

We present the results for the logit and random coefficients specifications of the discrete choice model of consumer demand for prepared frozen meals. The logit model provides an easy-to-estimate reference point despite the restrictive substitution patterns that it generates. The random coefficients model allows for more flexible substitution effects by considering interactions between consumer and product characteristics.

To estimate the two models, we use data for the 200 products with the highest national sales in all of the quarters from 1993 to 1998. The combined share of these 200 products varies from 62 to 65 percent of the total national sales of prepared frozen meals in each quarter.

The Logit Model

First, we present the logit model results and evaluate the importance of instrumenting for price and the effects of the different sets of instruments used. Table 5 shows the estimates obtained by regressing the market share of a particular product relative to the outside good share ($\ln(S_{jt})$-$\ln(S_{0t})$) on product characteristics (including price), advertising and in-store marketing efforts, product specific dummies, and consumer characteristics (including consumer knowledge about fat and nutrition panel use). The dependent variable can also be interpreted as the probability a consumer will choose a particular product among the alternatives and the outside good. In the first column of Table 5, we report the results of ordinary least squares regression applied to the logit utility specification for 4,800 observations (200 products in 24 quarters, 1993-1998). In the second and third column, we re-estimate the logit utility specification to account for the possible correlation between the price variable and the unobserved characteristics (or $\Delta\xi_{jt}$ in our case) by using an instrumental variable estimation technique. In the second column, we use the average product price as an instrument in a two stage least squares regression. In the third column, we use a different instrument: a lagged value of price.

The use of instruments generates changes in several of the parameter estimates. Most importantly, the coefficient on price more than triples and thus shows a dramatic increase in absolute value. The coefficient on price is similar in the two regressions that use instruments. The first stage

R^2 and F-statistics for the instrumental variable regressions are high, suggesting that the instruments we use have some explanatory power. The results indicate that correcting for the possible endogeneity of prices is important. We can also see the importance of unobservables ($\Delta\xi_{jt}$) by examining the fit of the logit model. The instrumental variable method gives a first stage R^2 of 0.88. This implies that only 12 percent of variance in mean utility levels is due to the unobserved characteristics ($\Delta\xi_{jt}$).

In our modeling of consumer choice of prepared frozen meals, we include consumer characteristic variables to account for the heterogeneity of consumer preferences. In the logit specification, these variables enter the model only through the error term. Therefore, their inclusion eliminates the omitted-variable bias in the mean of consumer utility. The coefficients on the consumer characteristic variables show the change in the valuation of frozen meals as a function of these characteristics. The results suggest that the valuation of frozen meals significantly increases with consumer household size and significantly decreases with consumer income. Increases in general and specific fat knowledge, and age decrease consumer valuation of frozen meals. However, these changes are statistically insignificant. Finally, the positive coefficient on the nutrition panel use variable suggests that consumer valuation of frozen meals increases with increased use of nutrition panels but the coefficient is not statistically significant.

The logistic regression also includes the advertising variable, which has a positive and statistically significant coefficient. With the exception of the OLS specification, the estimated effect of advertising is almost the same in all specifications. A larger value of the advertising coefficient in the OLS column is a result of the correlation between unobserved characteristics and advertising: brands with larger market shares tend to have higher unobserved “quality” and are advertised more.

Table 5. Estimates of the Logistic Discrete Choice Model, 1993-1998.

Variable	OLS	Instrumental Variable Method	
		Average Quarterly Price	Lagged Price
Calories	0.020* (4.3211)	0.031* (4.0655)	0.029* (4.2598)
Fat (g)	0.011* (5.3872)	0.008* (4.6881)	(0.011)* (4.7210)
Cholesterol (mg)	0.001 (0.9677)	0.010 (1.0032)	0.012 (1.1312)
Sodium (mg)	-0.076* (-6.3440)	-0.035* (-4.3265)	-0.043* (-4.5195)
Fiber (g)	0.004 (0.8972)	0.003 (0.6488)	0.002 (0.7484)
Protein (g)	0.094 (0.7947)	0.052 (0.4276)	0.072 (0.6430)
Vitamin A (%)	0.011 (0.3329)	0.017 (0.4021)	0.015 (0.3877)
Vitamin C (%)	0.037 (0.4046)	(0.020) (0.5236)	0.019 (0.5431)
Meat Dummy (=1 if Contains Meat)	0.309* (4.4090)	0.192* (3.6353)	0.215* (4.0276)
Ethnic Dummy (=1 if Ethnic Food)	0.499* (3.9344)	0.302* (3.4868)	0.278* (2.9769)
Package Size (oz)	-0.016 (-0.3482)	-0.001 (-0.2046)	-0.002 (-0.3011)
Price ($ per serving)	-5.312* (-3.9675)	-18.540* (-4.2127)	-18.041* (-3.9943)
Advertising (M$)	0.062* (3.1196)	0.057* (3.2016)	0.059* (3.1524)
Price Reduction (%)	0.162* (2.6751)	0.202* (2.5882)	0.207* (2.4922)
Display (%)	0.252 (1.4660)	0.342 (1.5020)	0.320 (1.5242)
Feature (%)	0.092 (1.3310)	0.039 (1.2430)	0.043 (1.3042)
General Fat Knowledge	-0.345 (-1.3667)	-0.322 (-1.4137)	-0.316 (-1.3870)

Specific Fat Knowledge	-0.003 (-0.3603)	-0.001 (-0.2595)	-0.001 (-0.3141)

Table 5. Estimates of the Logistic Discrete Choice Model, 1993-1998. (Continued)

Variable	OLS	Instrumental Variable Method	
		Average Quarterly Price	Lagged Price
Nutrition Panel Use	0.246 (0.9866)	0.036 (0.8739)	0.152 (0.9452)
Log of Income	-0.986* (-2.8524)	-0.759* (-2.7966)	-0.732* (-2.5442)
Log of Age	-0.003 (1.0114)	-0.001 (0.8941)	-0.001 (0.9205)
Household Size	0.493* (2.2930)	0.503* (2.6492)	0.501* (2.6381)
R^2 (adjusted)	0.64	0.87	0.88
F-statistic	2474	3160	3302

Dependant variable is $\ln(S_{jt}) - \ln(S_{0t})$.
*Significant at the 5% level (two-tailed test).
The t-values are in parentheses.
All regressions include time dummy variables that are statistically insignificant.

Once we control for this potential endogeneity, the values of the coefficients are almost the same. Non-linear effects in advertising were also tested and were found to be statistically insignificant.

The purpose of the logit model is mainly diagnostic, therefore, we now turn to the analysis of the results obtained from the random coefficients model.

The Random Coefficients Model

The estimated parameters of the random coefficients model are presented in Table 6, again for 4,800 observations. They are derived from the utility function specified by equation (3). The variables that enter this utility function are the same as those presented in Table 5. However, now, the marginal utility derived from each attribute varies across consumers so that we estimate a mean and a variance for each of the attributes. The dependent variable is again the market share of a particular product relative to the outside good market share or, alternatively, the probability a consumer will choose a particular product among the alternatives and the outside good.

The first two rows of Table 6 provide estimates of the means and standard deviations of the marginal utility distributions for each attribute. The mean coefficients on product characteristics are retrieved by a minimum distance regression of the GMM product specific dummy coefficients on product characteristics (Chamberlain 1982). The next five rows provide the estimated parameters that measure interactions between consumer and product characteristics. The means of the distribution of marginal utilities, β, are all statistically significant except for in-store display, featuring, and package size.

These results show that for the average consumer, both calories and fat have a positive effect on marginal utility. Products containing meat and products that can be characterized as ethnic foods also have a positive effect on consumer marginal utility. On the other hand, sodium has a negative effect for the average consumer. Our findings with respect to calories and fat can be attributed to strong consumer preferences for taste as opposed to their concerns about nutrition and health.

While the estimates of standard deviations of marginal utilities, σ, are not statistically significant, the results show that most interactions with the demographic variables are significant. This suggests that heterogeneity in the coefficients is mostly explained by the included demographic variables, most importantly income and household size. Marginal utility from sodium decreases with increases in income. Consumer preferences for calories, fat, meat, and ethnic foods increase with increased income and household size.

The mean price coefficient is negative and thus shows that for the average consumer utility decreases with price increases. Coefficients on the interactions of price with demographics are

Table 6. Estimates of the Random Coefficients Discrete Choice Model, 1993-1998.

Component	Variable	Estimate	t-Statistics
Means (β's)	Price	-16.041*	-3.4766
	Advertising	0.054*	3.1834
	Price Reduction	0.187*	2.3633
	Display	0.252	1.4861
	Feature	0.036	1.2574
	Constant	-2.217*	-2.9477
	Calories	0.023*	4.1763
	Fat	0.009*	4.5956
	Sodium	-0.040*	-4.2172
	Meat Dummy	0.189*	3.0001
	Ethnic Dummy	0.258*	2.5723
	Package Size	-0.002	-0.2644
Standard Deviations (σ's)	Price	0.103	1.4121
	Constant	0.025	1.2765
	Calories	0.001	1.3561
	Fat	0.001	1.3985
	Sodium	0.006	1.5002
	Meat Dummy	0.075	1.3127
	Ethnic Dummy	0.064	1.6002
	Package Size	0.001	0.6833
Interaction with Income	Price	17.052*	4.7672
	Constant	-0.546*	-3.8238
	Calories	0.019*	2.0024
	Fat	0.001*	1.5965
	Sodium	-0.012*	-1.6983
	Meat Dummy	0.020*	1.6675
	Ethnic Dummy	0.019*	2.4733
Interaction with Income^2	Price	-12.601*	-5.9140
Interaction with Household Size	Price	-19.655*	-2.1360
	Constant	-0.079*	-2.7688
	Calories	0.002*	1.7650
	Fat	0.022*	1.7264
	Sodium	-0.016*	-1.7583
	Meat Dummy	0.017	1.5827
	Ethnic Dummy	0.005	1.6004
Interaction with Household Size^2	Price	10.437	2.9626
Interaction with General Fat Knowledge	Price	-0.136	-0.6241
	Constant	-0.053	-0.8566
	Calories	-0.001	-0.3287
	Fat	-0.001	-0.1453
	Sodium	-0.003	-0.5611
	Meat Dummy	0.007	0.7925
	Ethnic Dummy	0.002	0.4001

Table 6. Estimates of the Random Coefficients Discrete Choice Model, 1993-1998. (Continued)

Component	Variable	Estimate	t-Statistics
Interaction with Specific Fat Knowledge	Price	0.102	0.4632
	Constant	-0.027	-0.5810
	Calories	-0.000	-0.0476
	Fat	-0.001	-0.0845
	Sodium	-0.008	-0.3798
	Meat Dummy	-0.003	-0.3007
	Ethnic Dummy	0.001	0.2658
Interaction with Nutrition Panel Use	Price	-0.099	-0.5377
	Constant	-0.016	-0.6331
	Calories	-0.001	-0.1480
	Fat	-0.001	-0.1702
	Sodium	-0.006	-0.3960
	Meat Dummy	0.012	0.5300
	Ethnic Dummy	0.004	0.3428
GMM Objective Function		7.26	
Minimum Distance χ^2		2413	
% of Price Coefficients >0		33	

Dependant variable is $\ln(S_{jt}) - \ln(S_{0t})$.
* significant at the 5% level (two-tailed test).
All regressions include time dummy variables that are statistically insignificant.

statistically significant. Consumers with above average income tend to be less price sensitive as do smaller households.

The mean coefficients on advertising, price reduction, in-store display, and featuring are positive. Advertising and price reduction have a significant effect on consumer valuation of frozen meals, while in-store display and featuring do not. Non-significant coefficients on these latter variables may be related to a higher correlation between the price reduction and display and featuring variables.

Consumer utility from the outside good is measured by the constant term. Consumers with above average income and larger households are less likely to buy prepared frozen meals and value the outside option higher.

The estimated coefficients on both fat knowledge variables and on the nutrition panel use variable are negative but statistically insignificant (Table 6). Thus, knowledge about fat, whether in general or specific form, and nutrition panel use, have no significant effect on how consumers choose prepared frozen meals. We also tested the interaction of the fat knowledge variables with the product characteristic variables. Again none of the interaction variables were statistically significant. These results provide further evidence that knowledge about fat and nutrition panel use, at least as specified here, have no significant impact on consumer choices. We plan to explore alternative specifications of the nutrition knowledge variables. For example, Variyam et al. (1996) found that nutrition knowledge was not a significant factor for dietary fiber intake but that nutrition awareness and attitude towards nutrition was significant.

In all regressions, we include zero-one time dummy variables to account for possible structural changes in consumer preferences in the period before and after the implementation of mandatory nutrition labeling. None of the time-dummy variables are statistically significant. Therefore, the results of this test for structural change show that, in the period under examination, no significant changes occurred in consumer preferences for prepared frozen meals. Increases in the quantity and quality of information available to consumers after the implementation of mandatory labeling requirements did not significantly alter consumer preferences and purchasing patterns.

Table 7 presents a sample of the calculated demand elasticities with respect to the continuous attributes of frozen meals, their own prices, and advertising. The elasticities are computed based on equations (6) and (11), and on the estimates of the coefficients reported in Table 6. For each attribute, the left column shows the value of that attribute per serving and the right column shows the calculated elasticity. The elasticities for price and sodium are negative and the elasticities for calories, fat, and advertising are positive. Each entry gives the percentage change in market share of the product with a one percentage change in its own price, its own product attributes, and its own advertising. For example, the top of Table 7 shows that for the average product a 1 percent increase in price, holding other variables constant, would result in a 2.43 percentage point decrease in market share of this product. An increase of 1 percent in fat content would lead to a 0.11 percentage point increase in market share. We can conclude that, on average, changes in prices and advertising would lead to the largest changes in market shares. On the other hand, changes in the nutritional characteristics of products would lead to relatively small changes in market shares. This means that consumers are less sensitive to changes in nutritional characteristics than to changes in prices and advertising.

Table 7. A Sample of the Calculated Demand Elasticities for the Continuous Attributes, Prices, and Advertising.

	Price/Serving		Advertising		Calories/Serving		Fat/Serving		Sodium/Serving	
Descriptive Statistics[a]										
Mean	-2.43		0.23		0.15		0.11		-0.09	
Std	0.83		0.12		0.20		0.09		0.10	
Product[b]										
1	3.51	-3.72	106.4	0.19	220.00	0.12	12.00	0.14	616.00	-0.18
2	3.02	-3.21	106.4	0.19	199.00	0.11	9.00	0.12	500.00	-0.12
5	2.05	-2.27	0	0.00	280.70	0.15	16.00	0.18	900.16	-0.26
10	1.13	-1.54	0	0.00	219.44	0.12	10.80	0.13	505.00	-0.12
100	2.27	-2.58	0	0.00	123.80	0.07	2.00	0.01	209.50	-0.04

For each variable the left column presents the value of the attribute in dollars, million of dollars, calories, grams, and milligrams respectively.
[a] Descriptive statistics of elasticities in all quarters.
[b] A sample of elasticities for the last quarter of 1998.

Implications for Price Competition and Government Policy

In this section, we examine the implications of the estimated demand system first for price competition in the prepared frozen meals industry and second for government policies that require the provision of information about the nutritional quality of food products.

Price Competition

To examine the nature of price competition, we compute the price cost margins (PCM) implied by three hypothetical industry structures: single product firms, a few firms producing many products each (the current structure of the industry), and one firm producing all of the products. The margins in the first structure result from product differentiation only. The margins in the second structure also include the multi-product firm portfolio effect. Finally, in the last structure, the margins are due to joint ownership or full collusion (Nevo 1997). We use information on production costs from the Annual Survey of Manufacturers for 1993-1998 to compute the actual PCMs and evaluate which of the firm conduct models best fits these margins.

We take as given that there are F firms in the market, each of which produces some subset of the J frozen prepared meals. Given the demand system specified in the previous section, the profits of firm f, Π_f, are:

(15) $$\Pi_f \quad {}_{j \varepsilon F_f} (p_j \quad mc_j) M s_j(p) \quad C_f,$$

where $s_j(p)$ is the market share of product j, M is the size of the market, and C_f are the fixed costs of production. Each firm is assumed to choose prices that maximize its profit given the attributes of its products and the prices and attributes of competing products. In addition, we assume that a Bertrand-Nash equilibrium exists in this pricing game, and that the equilibrium prices are in the interior of the firms' strategy sets.

Any product produced by firm f, must have a price, p_j, that satisfies the following first order conditions:

$$(16) \qquad s_j(p) + \sum_{r \varepsilon F_f} (p_r - mc_r) \frac{\partial s_r(p)}{\partial p_j} = 0.$$

These J first order conditions (or equations) imply price-cost markups (p-mc) for each good. The markups can be obtained by defining $S_{jr}=-\partial s_r/\partial p_j$ $j, r=1,\ldots,J$,

$$(17) \qquad \Omega_{jr} = \begin{cases} 1, & if \ \exists f: (rj) \subset F_f; \\ 0, & otherwise \end{cases}$$

and $\Omega_{jr}=\Omega^*_{jr}S_{jr}$. In vector notation the first order conditions can be written as

$$(18) \qquad s(p) - \Omega (p - mc) = 0.$$

Therefore, we get the following price-cost markup equation

$$(19) \qquad p - mc = \Omega^{-1} s(p).$$

In the above equation, the markups depend only on the parameters of the demand system and the equilibrium price vector. Given the demand parameters, we compute the price-cost margins in the prepared frozen meals industry as (p-mc)/p and we distinguish between three different sources of the margins: the effect due to product differentiation, the effect due to product proliferation, and the effect due to potential price collusion. In the first case, we answer the question what the margins would be if each product were produced by a different single product firm. Under this scenario, the margins are due only to the own price elasticities of products. In the second case, a few multi-product firms take into account substitution between the different products they produce when setting prices. If products are substitutes, a multi-product firm will set a higher price than a single product firm, taking into consideration the possible externalities created by price increases of its own products. The difference between the margins in this case and in the first case is due to product proliferation. Lastly, we can consider a third case, where all existing products are produced by the same firm. This places an upper bound on the effect of price collusion given the estimated demand structure.

Table 8 reports the computed mean price-cost margins for the logit model and for the random coefficients model for the three hypothetical industry structures described earlier. These results present the PCMs that different models of pricing conduct predict, taking as given products offered for sale, their characteristics, and firms' advertising. The random coefficients model provides more plausible estimates of the cross-price elasticities than the logit model, therefore, the difference in margins that these two models imply increases as we move from single- to multi-product firms, and then to a joint ownership structure.

Table 8. Computed Mean Price-Cost Margins* for Three Hypothetical Industry Structures.

Hypothetical Industry Structure	Logit Model (%)	Random Coefficients Model (%)
Single Product Firms	25.6	27.2
A Few Multi-Product Firms	28.5	31.5
Joint Ownership of 200 Products Considered	34.1	47.8

*Margins are defined as (p-mc/p) and are % gross margins.

In order to determine which model of conduct best fits the observed margins in the prepared frozen meals industry, we compare the values from Table 8 to the estimates of the actual price-cost margins for the industry presented in Table 9. We construct estimates of the actual margins based on the Annual Survey of Manufacturers for 1993-1998. This survey reports the average variable cost only, therefore, the gross margins shown in Table 9 can be treated as an upper bound on PCMs. If we assume that firms produce at the minimum efficient scale and that their cost curves are U-shaped, then the marginal cost will be higher than the average cost, and the margins evaluated at the marginal cost will be lower than the margins evaluated at the average cost.

Table 9. Aggregate Estimates of Manufacturers' Production Costs, 1993-1998.

Item	Prepared Frozen Meals Industry		All Food Industries	
	Million $	% of Value	Million $	% of Value
Value of Shipments	5, 431	100.0	461,324	100.0
Materials	3,199	58.9	283,714	61.5
Labor	489	9.0	42,442	9.2
Energy	92	1.7	5,997	1.3
Gross Margin	1,651	30.4	129,171	28.0

A comparison of the values of margins shown in Tables 8 and 9 leads us to the conclusion that a multi-product Nash-Bertrand equilibrium in prices is consistent with the actual PCMs in the prepared frozen meals industry. The possibility of collusive pricing behavior undertaken by manufacturers can be rejected, because the actual margins are much lower than those implied by the joint ownership structure. This suggests that the 30% margins in the industry are due to product proliferation and differentiation strategies. Manufacturers are able to differentiate their products from competitors and are able to influence the perceived quality of the products in order to increase consumer willingness to pay. At the same time, it appears that substitution patterns between manufacturers' own products are very important in price setting decisions. The results of this test of pricing behavior exclude an extreme version of cooperative pricing where all firms jointly maximize profits. However, there is a continuum of pricing models that were not tested here. For example, our results do not exclude cooperative pricing between a subset of products or producers. The methods and tests used here could deal with these additional pricing models but would require more detailed cost data.

Government Labeling Policy

Our model is defined in terms of a utility function that assigns values to different possible combinations of product characteristics as a function of consumer characteristics. We compute own- and cross-price elasticities as well as elasticities of demand with respect to product attributes for all of the products considered. The results have important implications for analysis of the effectiveness of government regulation of nutrition labeling of processed foods.

The analysis of consumer preference parameters for the nutritional attributes of prepared frozen meals reveals that consumers value only a very few nutritional characteristics of these products. Both calories and fat are valued positively but sodium is valued negatively. Products containing meat and products that can be characterized as ethnic foods are also valued positively. Our findings with regard to the positive valuation of calories, fat, products containing meat, and ethnic foods can be linked to strong consumer preferences for taste as opposed to nutrition and health-related attributes.

The calculated elasticities of demand show that product prices and advertising play a much greater role in consumer choices of prepared frozen meals than do nutritional characteristics. Nor does consumer knowledge about fat and nutrition panel use appear to have a significant impact on consumer choices.

The results of our test for structural change show that, in the period under consideration, no significant changes occurred in consumer preferences for prepared frozen meals. Therefore, we conclude that the increased quantity and improved quality of information available to consumers after the implementation of mandatory nutrition labeling did not lead to changes in consumer preferences and purchasing patterns.

The new mandatory labeling policy was implemented in order to give consumers a tool to learn more about the nutritional quality of the foods they eat. Ultimately, the labeling policy was meant to encourage consumers to demand foods with better nutritional profiles. Based on our results, it appears that to date the mandatory nutritional labeling policy has been ineffective in influencing consumer demand for prepared frozen meals. The investment already made in nutrition labeling might generate a larger payoff with a more active educational campaign.

Extensions of this Research

The methods we use in this paper allow us to obtain more plausible demand parameters by considering product and consumer heterogeneity. The estimated parameters are crucial for the evaluation of many policy issues. In this sense, our work might provide a useful tool leading to a more realistic and accurate analysis of producer and consumer behavior in the market place than that obtained by previous models. However, our approach is also limited, especially in regards to the treatment of dynamics. On the producer side, the problem is to endogenize the actual choice of the product characteristics and advertising. Even the more detailed models of dynamic industry equilibria (e.g., Pakes and McGuire 1994) still have to be developed further before they can provide a real world approximation of the multi-product, multi-characteristic nature of the food industry. On the consumer side, a complete model of dynamic decision making would incorporate both transaction costs and uncertainty.

References

Anderson, S., A. De Palma, and F. Thisse. 1989. Demand for Differentiated Products, Discrete Choice Models, and the Characteristics Approach. *Review of Economic Studies*, 56:21-35.

Berry, S. 1994. Estimating Discrete Choice Models of Product Differentiation. *RAND Journal of Economics*, 25:242-262.

Berry, S., J. Levinsohn, and A. Pakes. 1995. Automobile Prices in Market Equilibrium. *Econometrica*, 63:841-890.

Bresnahan, T. 1987. Competition and Collusion in the American Automobile Oligopoly: the 1955 Price War. *Journal of Industrial Economics*, 35:457-482.

Cardell, N. S. 1989. *Extensions of the Multinomial Logit: the Hedonic Demand Model, the Non-Independent Logit Model, and the Ranked Logit Model*. Ph.D. Dissertation, Harvard University.

Chamberlain, G. 1982. Multi-Variate Regression Models for Panel Data. *Journal of Econometrics*, 18(1):5-46.

Cotterill, R. W. 1996. High Cereal Prices and the Prospects for Relief by Expansion of Private Label and Antitrust Enforcement. Testimony offered at the Congressional Forum on the Performance of the Cereal Industry, Washington D.C., March 12.

Dixit, A. and J. Stiglitz. 1977. Monopolistic Competition and Optimum Product Diversity. *American Economic Review*, 67:297-308.

Gorman, M. 1959. A Possible Procedure for Analyzing Quality Differentials in the Egg Market. *Review of Economic Studies*, 47:843-56.

Hausman, J. 1996. Valuation of New Goods Under Perfect and Imperfect Competition. In T. Bresnahan and R. Gordon, eds., *The Economics of New Goods*, Studies in Income and Wealth, Vol.58, Chicago: National Bureau of Economic Research.

Hausman, J., G. Leonard, and J. D. Zona. 1994. Competitive Analysis with Differentiated Products. *Annales D'Economie et de Statistique*, 34:159-80.

McFadden, D. 1978. Modeling the Choice of Residential Location. In A. Karlgvist, et al. Eds., *Spatial Interaction Theory and Planning Models*, Amsterdam: North-Holland.

Mojduszka, E., J. A. Caswell, D. B. West, and J. M. Harris. 1999. Changes in Nutritional Quality of Food Product Offerings and Purchases. A Case Study in the Mid-1990's. An Economic Research Service Report, Technical Bulletin #1880. United States Department of Agriculture, Washington DC.

Nevo, A. 1998. A Research Assistant's Guide to Random Coefficients Discrete Choice Models of Demand. NBER Technical Paper no. 221.

Nevo, A. 1997. *Demand for Ready-to-Eat Cereal and Its Implications for Price Competition, Merger Analysis, and Valuation of New Goods*. Ph.D. Dissertation, Harvard University.

Pakes, A. 1986. Patents as Options: Some Estimates of the Value of Holding European Patent Stocks. *Econometrica*, 54:755-784.

Pakes, A. and McGuire. 1994. Computation of Markow Perfect Nash Equilibria I: Numerical Implications of a Dynamic Product Model. *RAND Journal of Economics*, 25:555-589.

Perloff, J. and S. Salop. 1985. Equilibrium with Product Differentiation. *Review of Economic Studies*, 52:107-120.

Shaked, A. and J. Sutton. 1982. Relaxing Price Competition Through Product Differentiation. *Review of Economic Studies*, 49:3-13.

Spence, M. 1976. Product Selection, Fixed Costs, and Monopolistic Competition. *Review of Economic Studies*, 43:217-235.

Variyam, J. N., J. Blaylock, and D. Smallwood. 1996. A Probit Latent Variable Model of Nutrition Information and Dietary Fiber Intake. *American Journal of Agricultural Economics*, 78(August):628-639.